Medicaid and the Labor Supply of Single Mothers: Implications for Health Care Reform (Online Appendix)

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A Simulation Details

A.1 Multinomial Logit Estimation

The simulation based estimation algorithm described in Section 5.2 of the paper proceeds as follows:

1. Draw R simulation draws from the estimated distributions of the random individual effects and i.i.d. shocks in the wage, medical expenditure, and ESHI offer equations. In practice, $R = 100$.

2. Calculate annual consumption for each individual, simulation draw, and alternative. Determine for each individual and simulation draw if part-time and full-time job offers include ESHI. Determine for each individual, simulation draw, and alternative if the mother and her children are eligible for Medicaid or CHIP.

3. For each individual, alternative, and simulation draw I can then calculate the alternative-specific utility based on initial guesses for the preference parameters. Given the distributional assumption, the choice probabilities have a MNL form.

4. Estimate the fixed preference parameters and the distribution of the random preference parameters using MSL (see below for details).

Since estimation of the preference parameters is based on using independent variables that are derived from first-stage regression, regular standard errors are not valid. Instead, standard errors of the coefficients in all regressions are obtained using block-bootstrap to account for clustering within state.

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The parameters of the MNL are estimated as follows: Let $X^{u,(r)}_{itj} = \left(\tilde{C}^{(r)}_{itj}, \tilde{H}_{itj}, I^{P,(r)}_{itj}, I^{K,(r)}_{itj}\right)$ denote the vector of utility function arguments for individual i, time t, and alternative j in simulation draw r. Given the distributional assumption about the error term η_{itj} in equation (12) in the text, the probability that individual i chooses alternative j at time t has the multinomial logit form conditional on the preference parameters $\left(\beta^C, \beta_i\right)$ and $\gamma = (\gamma_p, \gamma_{f_0}, \gamma_{f_1})$ and utility function arguments $X^{u,(r)}_{itj}$ for all alternatives:

$$p^{(r)}_{itj}\left(\beta^C, \beta_i\right) \equiv \Pr\left(d_{itj} = 1 | \beta^C, \beta_i, \gamma, \left\{X^{u,(r)}_{itk}\right\}_{k=n,p,f_0,f_1}\right) = \frac{\exp\left[u^{(r)}_{itj}\left(\beta^C, \beta_i\right)\right]}{\sum_{k=n,p,f_0,f_1} \exp\left[u^{(r)}_{itk}\left(\beta^C, \beta_i\right)\right]}, \quad (1)$$

where d_{itj} is an indicator for the chosen alternative and $u^{(r)}_{itj}$ is defined in equation (12). Hence the unconditional choice probability for individual i over both time periods averaging over simulation draws $r = 1, \ldots, R$ is

$$\pi\left(\delta, \Sigma; \left\{X^{u,(r)}_{itk}\right\}^{t=1,2}_{k=n,p,f_0,f_1}, Z^u_i\right) = \int_{\beta_i} \prod_{t=1}^{2} \prod_{j=n,p,f_0,f_1} \left[\frac{1}{R}\sum_{r=1}^{R} p^{(r)}_{itj}\left(\beta^C, \beta_i\right)\right]^{d_{itj}} d\mathbf{\Phi}\left(\beta_i | Z^\beta_i \delta, \Sigma\right), \quad (2)$$

where $\mathbf{\Phi}\left(\cdot | Z^\beta_i \delta, \Sigma\right)$ is the multivariate normal distribution with mean vector $Z^\beta_i \delta$ and variance-covariance matrix Σ.

Hence, the log-likelihood function is

$$LL(\theta) = \sum_{i=1}^{N} \ln \pi\left(\theta; \{X^u_{itk}\}^{t=1,2}_{k=n,p,f_0,f_1}, Z^\beta_i\right).$$

Since the log-likelihood function involves an integral over a three-dimensional normal distribution, no analytical expression is available. Instead, I simulate the log-likelihood function as follows:

$$SLL(\theta) = \sum_{i=1}^{N} \ln\left\{\frac{1}{R'}\sum_{r'=1}^{R'} \prod_{t=1}^{2} \prod_{j=n,p,f_0,f_1} \left[\frac{1}{R}\sum_{r=1}^{R} p^{(r)}_{itj}\left(\beta^{(r')}_i\right)\right]^{d_{itj}}\right\} \quad (3)$$

where $\beta^{(r')}_i$ is the r'th draw from the multivariate distribution $\mathbf{\Phi}\left(\cdot | Z^u_i \delta, \Sigma\right)$ and the choice probabilities based on R' such draws are averaged to obtain the likelihood contribution of each individual Train (2009).[1] The coefficients to be estimated are $\theta = \left(\delta, \Sigma, \beta^C, \gamma\right)$.

[1] I assume that the preference shocks are uncorrelated with the wage and expenditure shocks, so that the simulation draws are separate from the multivariate normal distribution of β_i and three additional error terms for the wage and

Then, the Maximum Simulated Likelihood estimation algorithm proceeds as follows:

1. Find starting values $\hat{\theta}^{(0)} = \left(\hat{\delta}^{(0)}, \hat{\Sigma}^{(0)}, \hat{\beta}^{C,(0)}, \hat{\gamma}^{(0)}\right)$ using multinomial logit with fixed parameters for $\hat{\delta}^{(0)}$, $\hat{\beta}^{C,(0)}$, and $\hat{\gamma}^{(0)}$ and setting the diagonal elements of $\hat{\Sigma}^{(0)}$ to one and its off-diagonal elements to zero.

2. Draw from $\mathbf{\Phi}\left(\cdot|Z_i^u\hat{\delta}^{(0)}, \hat{\Sigma}^{(0)}\right)$ R' times for each i and calculate the SLL according to equation (3).[2]

3. Maximize the SLL with respect to θ and obtain $\hat{\theta}^{(1)}$.

4. Iterate steps 2. and 3. until convergence.

I obtain the simulation draws at iteration (s) according to (Train, 2009, p. 208) as

$$\beta_i^{(r')} = Z_i^u\hat{\delta}^{(s)} + \hat{L}^{(s)}\nu_i^{(r')},$$

where $\hat{L}^{(s)}$ is the lower-triangular square matrix obtained from the Cholesky decomposition of $\hat{\Sigma}^{(s)} = \hat{L}^{(s)}\hat{L}^{(s)\prime}$, and $\nu_i^{(r')}$ is a vector drawn from the three-dimensional standard normal distribution. Instead of drawing pseudo-random numbers for $\nu_{it}^{(r')}$, I follow the suggestion by Bhat (2001) to use quasi-random numbers, in particular Halton sequences.[3] These sequences provide quasi-random draws from the uniform distribution, which are then transformed using the inverse of the standard normal density function to obtain the standard normally distributed $\nu_i^{(r')}$.[4] In practice, I set $R = R' = 100$.

Since the multinomial logit regression in the second step of my estimation procedure uses simulated regressors from the first step, conventional standard errors are incorrect. To obtain correct standard errors, I use a nonparametric block bootstrap. For each bootstrapped sample, I carry out the two-step estimation procedure described above and save the estimated parameter vector $\hat{\theta}$. Then I obtain standard errors as the square roots of the diagonal elements of the variance matrix of the $\hat{\theta}$-estimates. Since the exogenous variation is at the state-year level, drawing bootstrap samples at the individual level would lead to inconsistent standard errors. For correct inference,

the expenditure equations (which themselves are uncorrelated with each other).

[2] I keep the R draws for the wage and expenditure simulations and the R' draws for the preference parameters constant so that the choice probabilities $p_{itj}^{(r)}\left(\beta_i^{(r')}\right)$ only change through the distribution parameters at iteration s, $\hat{\delta}^{(s)}$ and $\hat{\Sigma}^{(s)}$.

[3] A Halton sequence results from dividing the unit interval by prime numbers. For example, for the prime 3, the first two elements of the sequence are 1/3 and 2/3. The resulting three intervals are further divided and yield 1/9, 2/9, 4/9, 5/9, 7/9, and 8/9 and so on. This sequence is not random, but pseudo-random numbers are not truly random either, so that a simulation estimator has the same properties using either method for drawing "random" numbers. Train (1999) shows that much fewer (e.g., 100 instead of 1000) simulation draws are necessary when using a Halton sequence versus pseudo-random numbers to obtain the same variance of the simulation estimator because Halton sequences cover the unit interval more evenly than pseudo-random numbers.

[4] In order to ensure proper values for the estimated variance-covariance matrix $\hat{\Sigma}^{(s)}$ at each iteration, i.e. positive values for diagonal elements and correlations between -1 and 1 for off-diagonal elements, I transform the estimated values using the formulae suggested by Haan and Uhlendorff (2006).

I follow Cameron, Gelbach, and Miller (2008) and draw clustered bootstrap samples at the state level (block bootstrap). This procedure accounts for dependence between individuals and across time within states.

A.2 Policy Simulation

To simulate labor supply and health insurance choices under the policy counterfactuals, I use the following algorithm:

1. Using the estimated parameters of the empirical model, I draw $R = 1000$ times from the conditional wage, medical expenditure, and ESHI offer probabilities.

2. I use these simulated wages, expenditures, and ESHI offer probabilities to calculate consumption and Medicaid eligibility according to the budget constraint (2) in the paper and eligibility conditions (5) and (6) in the paper under pre-ACA policies and the three policy counterfactuals.[5]

3. I simulate preference parameters by drawing $S = 1000$ times from the estimated distribution of the unobserved preference terms $\boldsymbol{\xi^U}$, $\mathcal{N}\left(\boldsymbol{Z_i^U}\hat{\boldsymbol{\delta}}, \hat{\Sigma}\right)$, for each individual, where $\hat{\boldsymbol{\delta}}$ and $\hat{\Sigma}$ are the estimated coefficients reported in Table 7.

4. I calculate the utility for every individual i, time period t, simulation draws r and s, and alternative j under policy pol, $U_{itj}^{pol,(r,s)}$, according to the utility function (8) in the paper.

5. For each individual, year, and simulation draws, I calculate the alternative with the highest utility under each policy, and average over i, t, r, and s for each alternative that is in the simulated choice set under the respective policy ($j \in J_{it}^{pol,(r)}$):

$$\bar{d}_j^{pol} = \frac{1}{NS} \sum_{i=1}^{N} \sum_{s=1}^{S} \frac{1}{T_i} \sum_{t=1}^{T_i} \frac{1}{R} \sum_{r=1}^{R} \mathbf{1}\left\{ j = \arg\max_k \ U_{itk}^{pol,(r,s)}, k \in J_{it}^{pol,(r)} \right\}. \tag{4}$$

B Results for Stepwise Estimation Approach

In this section, I present the results for the stepwise estimation approach described in Section 5.2 in the paper. Tables 1 and 2 shows the estimated coefficients from the first-step MNL models. Non-work is the baseline labor supply alternative, so the reported coefficients correspond to the effect of the regressors on choosing part-time and full-time employment with and without ESHI, respectively, relative to non-work. While I use these estimates to obtain the selection correction terms in the wage and expenditure equations below, these results are also interesting in their own right as

[5] Since the MEPS data come from a 15 year period, I use the FPL that was in effect in the respective year to simulate Medicaid eligibility thresholds. In other words, Medicaid eligibility is simulated as if the health care reform had been in effect since 1996.

they provide reduced-form evidence on the effect of Medicaid and other policies on labor supply. Specifically, Table 1 shows that more generous eligibility thresholds for parental and children's Medicaid increase the probability that single mothers work part-time and full-time although only one of the four coefficients is statistically significant. It is possible that the welfare parameters that are also included in this regression pick up some of the effect of Medicaid generosity, because Medicaid and welfare rules are positively correlated. This result is consistent with the findings in Ham and Shore-Sheppard (2005). Individual characteristics have the expected impact on labor supply, with more highly educated single mothers and those with older children more likely working full time, for example. Moreover, having more medical conditions makes women less likely to work.

Table 1: First-Step Multinomial Logit of Employment Choice

	Part-time		Full-time	
	No ESHI	ESHI	No ESHI	ESHI
Age	0.274***	0.139	0.196***	0.522***
	(0.0539)	(0.0920)	(0.0434)	(0.0461)
Age squared	−0.407***	−0.150	−0.293***	−0.676***
	(0.0748)	(0.119)	(0.0597)	(0.0614)
Black	−0.266**	−0.214	−0.149	−0.168*
	(0.113)	(0.190)	(0.0961)	(0.0926)
Hispanic	−0.420***	−0.854***	−0.173	−0.488***
	(0.128)	(0.257)	(0.106)	(0.108)
Years of education	0.131***	0.294***	0.0934***	0.340***
	(0.0222)	(0.0418)	(0.0178)	(0.0195)
Age of youngest child	0.0298	0.0429	0.0366**	0.0610***
	(0.0209)	(0.0359)	(0.0174)	(0.0172)
Number of children 0 to 2	−0.102	0.153	−0.134	0.309
	(0.247)	(0.505)	(0.200)	(0.231)
Number of children 3 to 4	0.282	0.460	0.112	0.453**
	(0.241)	(0.492)	(0.197)	(0.227)
Number of children 5 to 10	0.146	0.367	0.0681	0.425**
	(0.210)	(0.424)	(0.170)	(0.195)
Number of children 11 and older	0.148	0.460	0.165	0.415**
	(0.210)	(0.419)	(0.168)	(0.193)
Any medical condition, mother	0.166	−0.153	0.0574	−0.128
	(0.155)	(0.269)	(0.132)	(0.122)
Number of medical conditions, mother	−0.294***	−0.230*	−0.295***	−0.181***
	(0.0721)	(0.118)	(0.0612)	(0.0494)
Any medical condition, children	−0.273	−0.0672	−0.0153	−0.160
	(0.174)	(0.291)	(0.152)	(0.143)
Number of medical conditions, children	0.0383	−0.00641	−0.105	−0.0309
	(0.0829)	(0.137)	(0.0778)	(0.0688)
Medicaid eligibility threshold, parents (in $1,000)	0.847	0.709	0.687	0.996*
	(0.640)	(1.704)	(0.546)	(0.583)
Medicaid eligibility threshold, children (in $1,000)	0.110	0.135	0.272***	0.277***
	(0.0937)	(0.159)	(0.0767)	(0.0777)
State unemployment rate	−0.119**	−0.110	−0.234***	−0.214***
	(0.0592)	(0.102)	(0.0509)	(0.0492)
Log-minimum wage	−0.0659	−1.437	−1.047**	−0.798
	(0.611)	(1.121)	(0.531)	(0.520)
TANF benefit standard (in $1,000)	−0.0630	0.248	−0.0489	−0.222
	(0.365)	(0.649)	(0.301)	(0.311)
TANF gross income test percentage	−0.00452*	−0.00508	−0.00254	−0.00604***
	(0.00232)	(0.00388)	(0.00214)	(0.00198)
SNAP maximum benefit	0.000433	−0.00819	−0.00482	−0.00433
	(0.00741)	(0.0137)	(0.00616)	(0.00645)
SNAP eligibility gross income threshold	−0.00110	0.000652	0.000386	−0.00145
	(0.00224)	(0.00413)	(0.00186)	(0.00197)
Annual family ESHI premium (in $1,000)	−0.0358	0.138	0.585***	0.388**
	(0.192)	(0.352)	(0.160)	(0.162)
Annual family non-group premium (in $1,000)	0.0668	−0.0395	−0.132**	−0.0635
	(0.0728)	(0.132)	(0.0604)	(0.0622)
Constant	−4.065**	−4.007	−0.767	−7.924***
	(1.591)	(2.832)	(1.335)	(1.383)
Observations		13,869		

Notes: Estimated coefficients and standard errors (in parentheses) from a Multinomial Logit model of labor supply and health insurance choice with alternative-specific parameters. The baseline choice is non-work. * p<0.1, ** p<0.05, *** p<0.01.

Table 2: First-Step Multinomial Logit of Health Insurance Choice

	(Uninsured, Medicaid)	(Medicaid, Medicaid)	(Non-group HI, Medicaid)	(Non-group HI, Non-group HI)	(ESHI, Medicaid)	(ESHI, ESHI)
Age	0.0213	−0.100	−0.142	0.0407	0.194**	0.342***
	(0.0822)	(0.0734)	(0.121)	(0.102)	(0.0946)	(0.0794)
Age squared	−0.0369	0.0590	0.147	−0.0421	−0.249**	−0.446***
	(0.110)	(0.0973)	(0.164)	(0.132)	(0.125)	(0.104)
Black	0.502***	0.820***	0.915***	−0.969***	0.766***	0.0968
	(0.189)	(0.168)	(0.269)	(0.227)	(0.198)	(0.170)
Hispanic	0.627***	0.399**	0.308	−1.272***	−0.181	−0.362**
	(0.193)	(0.171)	(0.324)	(0.255)	(0.229)	(0.180)
Years of education	−0.0132	−0.0423	0.176***	0.300***	0.122***	0.401***
	(0.0308)	(0.0274)	(0.0565)	(0.0408)	(0.0372)	(0.0312)
Age of youngest child	−0.0614*	−0.0185	−0.0640	−0.0121	−0.0806**	0.0418
	(0.0323)	(0.0289)	(0.0516)	(0.0380)	(0.0354)	(0.0297)
Number of children 0 to 2	−0.266	0.233	−0.0966	0.0719	−0.0968	0.593
	(0.465)	(0.434)	(0.710)	(0.583)	(0.525)	(0.476)
Number of children 3 to 4	−0.211	−0.175	−0.0367	0.336	−0.270	0.416
	(0.439)	(0.408)	(0.681)	(0.546)	(0.501)	(0.450)
Number of children 5 to 10	−0.478	−0.311	−0.0149	0.251	−0.0986	0.198
	(0.374)	(0.349)	(0.598)	(0.470)	(0.424)	(0.387)
Number of children 11 and older	−0.718**	−0.487	−0.312	0.107	−0.196	−0.0270
	(0.360)	(0.335)	(0.593)	(0.457)	(0.411)	(0.373)
Any medical condition, mother	−0.0397	0.268	0.376	−0.0288	−0.166	0.162
	(0.267)	(0.233)	(0.373)	(0.289)	(0.287)	(0.239)
Number of medical conditions, mother	0.0793	0.298***	0.179	0.188	0.152	0.120
	(0.132)	(0.114)	(0.176)	(0.134)	(0.137)	(0.117)
Any medical condition, children	0.296	0.307	0.321	−0.190	0.252	0.207
	(0.306)	(0.280)	(0.443)	(0.339)	(0.330)	(0.286)
Number of medical conditions, children	0.0757	−0.0241	0.000947	0.0480	0.0155	−0.0476
	(0.158)	(0.148)	(0.230)	(0.165)	(0.171)	(0.150)
Medicaid eligibility threshold, parents (in $1,000)	0.331	0.321	−1.260	−0.303	0.220	−0.839
	(1.076)	(1.013)	(1.482)	(1.334)	(1.192)	(1.075)
Medicaid eligibility threshold, children (in $1,000)	0.0559	0.388**	0.307	0.104	0.411**	0.322**
	(0.179)	(0.157)	(0.242)	(0.192)	(0.178)	(0.162)
State unemployment rate	−0.0891	−0.0499	−0.189	−0.0622	−0.231**	−0.133
	(0.0987)	(0.0843)	(0.150)	(0.107)	(0.107)	(0.0862)
Log-minimum wage	−0.861	−0.0965	−1.976	1.454	−1.674	0.0288
	(1.125)	(1.013)	(1.632)	(1.279)	(1.204)	(1.039)

Continued on next page

Table 2 continued from previous page

	(Uninsured, Medicaid)	(Medicaid, Medicaid)	(Non-group HI, Medicaid)	(Non-group HI, Non-group HI)	(ESHI, Medicaid)	(ESHI, ESHI)
TANF benefit standard	0.194	1.681***	0.962	0.726	0.971	0.532
(in $1,000)	(0.645)	(0.571)	(0.915)	(0.734)	(0.666)	(0.596)
TANF gross income test	0.00323	−0.00386	−0.00809	0.0101**	−0.000952	−0.00469
percentage	(0.00488)	(0.00394)	(0.00652)	(0.00512)	(0.00497)	(0.00399)
SNAP maximum benefit	0.00270	0.0294**	0.0153	0.0313**	0.00302	0.0286**
	(0.0126)	(0.0115)	(0.0189)	(0.0147)	(0.0136)	(0.0122)
SNAP eligibility gross	0.00159	−0.00777**	−0.00424	−0.00919**	−0.000794	−0.00997***
income threshold	(0.00383)	(0.00350)	(0.00579)	(0.00449)	(0.00416)	(0.00375)
Annual family ESHI	−0.788**	−0.902***	−1.030**	−0.947***	−0.775**	−0.589**
premium (in $1,000)	(0.316)	(0.284)	(0.464)	(0.361)	(0.341)	(0.294)
Annual family non-group	0.418***	0.341***	0.576***	0.335**	0.430***	0.268**
premium (in $1,000)	(0.126)	(0.112)	(0.189)	(0.142)	(0.136)	(0.118)
Constant	−1.776	5.610**	4.495	−5.942*	−2.760	−5.300**
	(2.776)	(2.428)	(3.996)	(3.247)	(3.016)	(2.567)
Observations			10,893			

Notes: Estimated coefficients and standard errors (in parentheses) from a Multinomial Logit model of health insurance choice with alternative-specific parameters. The baseline choice is (Uninsured, Uninsured). * p<0.1, ** p<0.05, *** p<0.01.

As discussed in Section 5.2.1 in the paper, I estimate a separate MNL of health insurance choice to obtain selection correction terms for the medical expenditure regressions. The estimated coefficients for this model are reported in Table 2, where the baseline alternative is (uninsured, uninsured) and each column corresponds to a combination of health insurance coverage for mothers and children. Some of the policy parameters in this regression have predictive power, as shown by the negative correlation between ESHI premiums and the likelihood of obtaining private health insurance. Moreover, children's Medicaid generosity increases children's public health insurance coverage. On the other hand, higher non-group premiums also decrease the probability of being uninsured. Individual characteristics that explain health insurance status include years of education and being Hispanic, which respectively increase and decrease the likelihood of private coverage.

The results for two separate log-wage regressions for observed part-time and full-time employment choice with and without ESHI are reported in Table 3. As described in Section 5.2.2 in the paper, the wage regressions include third-order polynomials of the predicted choice probabilities based on the estimates shown in Table 1 (including all possible interactions), state fixed effects, and individual random effects. As expected, education has positive returns that are generally higher for full-time jobs. The return to education is exceptionally high among single mothers who work part-time with ESHI, but these individuals are likely very skilled because they would not receive any health benefits in a part-time job otherwise.

Tables 4 and 5 contain the estimates from two-part models of mothers' and children's out-of-pocket medical expenditure by observed health insurance coverage. As in the wage equation, I control for selection by including a flexible function of predicted choice probabilities, but in this case they are obtained from the MNL of health insurance choice (based on the estimates in Table 2). As expected, the number of medical conditions increases both the likelihood of having positive out-of-pocket medical expenditures and the amount of expenditures conditional on being positive, for both mothers and children. For mothers in particular, expenditures are more sensitive to the number of medical conditions among uninsured individuals. Hence, medical conditions are a suitable proxy for health insurance needs.

Next, Table 6 shows the Probit estimates for part-time and full-time ESHI offer probabilities. The variables that summarize the availability of ESHI on the state- and year-level have a positive but only marginally significant effect on individual ESHI offers. In particular, single mothers are more likely to receive an full-time job offer with ESHI if more firms offer health benefits. Moreover, the fraction of part-time and full-time employees who are eligible for ESHI in firms that offer it is positively correlated with ESHI offers. There is also a positive return to education in receiving job offers with health benefits, and minority women are generally less likely to obtain such offers.

In the final step of the stepwise estimation procedure, I estimate the preference parameters of the empirical utility function (8) in the paper via MNL with correlated random parameters (Mixed Logit). The estimated fixed preference parameter for log-consumption shown in the top panel of Table 7 is positive and statistically significant. The bottom panel of Table 7 contains the estimated

Table 3: OLS Regressions of Log-Wage by Observed Labor Supply and Health Insurance Choice

	Part-time		Full-time	
	No ESHI	ESHI	No ESHI	ESHI
Age	−0.00720	0.0732	−0.00515	−0.0282
	(0.0318)	(0.0660)	(0.0219)	(0.0221)
Age squared	0.0156	−0.00773	0.0207	0.0504
	(0.0475)	(0.0914)	(0.0324)	(0.0308)
Black	0.0516	−0.195*	−0.0938**	0.00909
	(0.0590)	(0.109)	(0.0403)	(0.0334)
Hispanic	0.0156	−0.502***	−0.0554	0.00360
	(0.0895)	(0.184)	(0.0648)	(0.0564)
Years of education	0.0307	0.273***	0.0761***	0.0941***
	(0.0231)	(0.0489)	(0.0151)	(0.0145)
Any med. condition, mother	0.0910*	−0.189	0.00422	0.0328
	(0.0548)	(0.122)	(0.0405)	(0.0325)
State unemployment rate	0.0890***	−0.107*	0.0191	0.0594***
	(0.0330)	(0.0634)	(0.0229)	(0.0196)
Log-minimum wage	0.971***	−1.200*	0.773***	0.818***
	(0.286)	(0.629)	(0.199)	(0.176)
Selection correction polynomial	X	X	X	X
State fixed effects	X	X	X	X
Individual random effects	X	X	X	X
Observations	1,957	472	3,031	4,601

Notes: Estimated coefficients and standard errors (clustered on the state-level, in parentheses) from OLS regressions of log-hourly wage. For each regression, the sample consists of single mothers whose observed labor supply and health insurance choice is part-time or full-time employment without or with ESHI. See Section 5.2 in the paper for a discussion of the selection correction approach. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Two-Part Regressions of Out-of-Pocket Medical Expenditure Regressions for Mothers

	$\mathbf{1}\{E > 0\}$				$\log(E)\|E > 0$			
	Uninsured	Medicaid	Non-group	ESHI	Uninsured	Medicaid	Non-group	ESHI
Age	0.0113	−0.0163	−0.0157	−0.0105	0.148	−0.195**	0.315*	−0.0123
	(0.0294)	(0.0153)	(0.0403)	(0.0179)	(0.120)	(0.0771)	(0.175)	(0.0787)
Age squared	0.00170	0.0359*	0.0204	0.0160	−0.134	0.269***	−0.303	0.0565
	(0.0367)	(0.0195)	(0.0489)	(0.0218)	(0.148)	(0.0977)	(0.211)	(0.0955)
Black	−0.140*	−0.0870**	−0.00259	−0.152***	−0.827**	−0.668***	−0.941*	−1.170***
	(0.0813)	(0.0415)	(0.117)	(0.0444)	(0.320)	(0.208)	(0.516)	(0.195)
Hispanic	−0.0691	−0.00607	0.0225	−0.0716	−0.505	0.326	0.0809	−0.891***
	(0.0813)	(0.0441)	(0.125)	(0.0501)	(0.313)	(0.224)	(0.532)	(0.224)
Years of education	−0.00557	0.00583	0.0304	0.0101	0.0651	−0.0911*	0.194	0.0562
	(0.0155)	(0.00940)	(0.0272)	(0.0121)	(0.0632)	(0.0481)	(0.121)	(0.0541)
Number of medical conditions, mother	0.0663***	0.0644***	0.0552**	0.0349***	0.255***	0.236***	0.0389	0.275***
	(0.0249)	(0.0128)	(0.0276)	(0.0111)	(0.0873)	(0.0600)	(0.116)	(0.0471)
Selection correction polynomial	X	X	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X	X	X
Individual random effects	X	X	X	X	X	X	X	X
Observations	2,444	4,998	677	2,774	1,182	2,339	299	1,308

Notes: Estimated coefficients and standard errors (clustered on the state-level, in parentheses) from two-part regressions of mothers' annual out-of-pocket medical expenditure (first part: Linear Probability Model of positive expenditure, second part: OLS of log-expenditure for positive expenditures). For each regression, the sample consists of single mothers whose observed health insurance choice is uninsured, Medicaid, or private. See Section 5.2 in the paper for a discussion of the selection correction approach. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Two-Part Regressions of Out-of-Pocket Medical Expenditure Regressions for Children

	$\mathbf{1}\{E > 0\}$				$\log(E)\|E > 0$			
	Uninsured	Medicaid	Non-group	ESHI	Uninsured	Medicaid	Non-group	ESHI
Black	−0.150	−0.118***	0.0224	−0.200***	1.547*	−0.357*	−1.002	−0.688**
	(0.177)	(0.0392)	(0.147)	(0.0580)	(0.828)	(0.198)	(0.684)	(0.270)
Hispanic	−0.0383	0.0118	−0.0840	−0.0697	1.566*	−0.414*	−1.622**	−0.353
	(0.199)	(0.0439)	(0.160)	(0.0685)	(0.857)	(0.229)	(0.758)	(0.312)
Years of education	0.0120	−0.00253	0.0188	0.0146	0.169	0.0554	−0.191	0.0306
	(0.0321)	(0.00856)	(0.0319)	(0.0147)	(0.143)	(0.0443)	(0.142)	(0.0694)
Number of medical conditions, children	0.127**	0.0965***	0.0256	0.0545***	0.332*	0.266***	0.145	0.268***
	(0.0536)	(0.0103)	(0.0232)	(0.0130)	(0.194)	(0.0462)	(0.0995)	(0.0560)
Number of children age 0 to 2	0.368***	0.0621**	0.0771	0.0960**	−0.628	−0.0253	−0.382	−0.220
	(0.130)	(0.0270)	(0.0958)	(0.0471)	(0.568)	(0.138)	(0.423)	(0.212)
Number of children age 3 to 4	0.259**	0.122***	0.133	0.0878**	−0.713	0.00517	−0.0793	0.0548
	(0.125)	(0.0271)	(0.0952)	(0.0430)	(0.504)	(0.142)	(0.428)	(0.193)
Number of children age 5 to 10	0.140**	0.0494***	0.0134	0.0572**	−0.233	0.0341	0.199	0.0465
	(0.0675)	(0.0150)	(0.0491)	(0.0258)	(0.275)	(0.0760)	(0.227)	(0.117)
Number of children age 11 and older	0.0509	0.0570***	0.00679	0.0561**	−0.472	0.169*	0.544**	0.331***
	(0.0705)	(0.0168)	(0.0513)	(0.0238)	(0.292)	(0.0866)	(0.250)	(0.109)
Selection correction polynomial	X	X	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X	X	X
Individual random effects	X	X	X	X	X	X	X	X
Observations	773	7,466	960	4,312	312	2,984	370	1,648

Notes: Estimated coefficients and standard errors (clustered on the state-level, in parentheses) from two-part regressions of the sum of children's annual out-of-pocket medical expenditure (first part: Linear Probability Model of positive expenditure, second part: OLS of log-expenditure for positive expenditures). For each regression, the sample consists of children of single mothers whose observed health insurance choice is uninsured, Medicaid, or private. See Section 5.2 in the paper for a discussion of the selection correction approach. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Probit Regressions of ESHI Offer Probabilities, by Observed Labor Supply Choice

	Part-time	Full-time
Age	0.00868	0.130***
	(0.032)	(0.0168)
Age squared	0.0187	−0.135***
	(0.0438)	(0.0229)
Black	0.130*	−0.0783**
	(0.0782)	(0.0392)
Hispanic	−0.216**	−0.234***
	(0.101)	(0.0456)
Years of education	0.115***	0.134***
	(0.0164)	(0.00716)
Percentage of firms offering ESHI	−0.0467	1.033*
	(1.155)	(0.597)
Percentage of part-time employees eligible for ESHI	0.339*	
	(0.204)	
Percentage of full-time employees eligible for ESHI		0.628*
		(0.349)
Constant	−2.770***	−5.269***
	(1.003)	(0.863)
State fixed effects	X	X
Individual random effects	X	X
Observations	2,429	7,632

Notes: Estimated coefficients and standard errors (clustered on the state-level, in parentheses) from Probit regressions of ESHI offers. For each regression, the sample consists of single mothers whose observed labor supply choice is part-time or full-time employment. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Parameter Estimates for Structural Mixed Multinomial Logit

Fixed preference parameter							
Log-consumption				0.0502***			
				(0.00561)			
Heterogenous preference parameters							
	Log-leisure	Medicaid, mother	Non-group, mother	ESHI, mother	Medicaid, children	Non-group, children	ESHI, children
Age	−0.00413*	−0.0444***	0.00973	0.0293***	0.499***	−0.941***	−0.186
	(0.0024)	(0.00381)	(0.00594)	(0.00453)	(0.127)	(0.213)	(0.155)
Black	0.151***	0.311***	0.0598	0.211*	0.369***	−0.798***	−0.387**
	(0.0398)	(0.0798)	(0.154)	(0.110)	(0.114)	(0.217)	(0.155)
Hispanic	0.383***	−0.308***	−0.769***	−0.835***			
	(0.0414)	(0.0767)	(0.163)	(0.117)			
Children under 4	0.364***						
	(0.0307)						
Med. conditions, mother		0.360***	0.190***	0.150***			
		(0.0294)	(0.0382)	(0.0316)			
Age of youngest child					−0.115***	−0.0368***	−0.0279***
					(0.00893)	(0.0129)	(0.0101)
Med. conditions, children					0.472***	0.339***	0.359***
					(0.0796)	(0.0912)	(0.0821)
Constant	−0.574***	2.240***	−1.816***	−1.522***	1.324***	2.233***	2.293***
	−0.0969	−0.138	−0.236	−0.185	(0.122)	(0.188)	(0.152)
Variance-covariance of preference shocks							
Log-leisure	1.101***						
	(0.0313)						
Medicaid, mother	0.405***	0.0452					
	(0.0494)	(0.0466)					
Non-group, mother	−0.444***	−0.0868	0.0604				
	(0.101)	(0.0867)	(0.0761)				
ESHI, mother	−0.771***	−0.0785	−0.0961**	0.0156			
	(0.0742)	(0.0616)	(0.0489)	(0.0489)			
Medicaid, children	0.183**	0.0937	0.159***	0.0507	0.0446		
	(0.0744)	(0.0701)	(0.0562)	(0.0549)	(0.0495)		
Non-group, children	0.342***	0.289**	0.0996	0.0224	−0.0337	0.0242	
	(0.129)	(0.117)	(0.106)	(0.0706)	(0.0646)	(0.0470)	
ESHI, children	0.140	0.0944	0.236***	0.0106	−0.0346	0.0378	0.0368
	(0.0928)	(0.0853)	(0.0725)	(0.0724)	(0.0526)	(0.0302)	(0.0283)

Notes: The first panel shows estimates of the fixed preference parameter. The second panel shows estimates of the effects of observables on preference parameters and estimates of the variance-covariance matrix of the unobserved preference components (see equations (8) and (9) in the paper for the functional form and distributional assumptions for the utility function and preference parameters). Block-bootstrapped (on the state level) standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Marginal Effects of Observable Characteristics From Mixed Multinomial Logit (in Percent)

	Non-work						
	(U, U)	(U, M)	(M, M)	(N, M)	(N, N)		
Age	0.0192	0.0771	−0.384	0.0150	0.0311		
	(0.0269)	(0.0764)	(0.125)	(0.0102)	(0.0317)		
Black	−0.570	0.276	0.0553	0.128	−0.0162		
	(0.488)	(0.654)	(0.0165)	(0.0988)	(0.896)		
Hispanic	0.0103	0.0403	0.0662	0.0746	−0.0138		
	(0.900)	(0.0137)	(0.0244)	(0.153)	(0.946)		
Children under 4	0.609	0.0137	0.0412	0.250	0.611		
	(0.454)	(0.774)	(0.0187)	(0.117)	(0.464)		
Med. conditions, mother	−0.358	−0.999	0.0172	−0.0306	−0.0594		
	(0.231)	(0.575)	(0.701)	(0.0274)	(0.0777)		
Age of youngest child	0.160	−0.0947	−0.273	−0.0161	0.0779		
	(0.109)	(0.0568)	(0.105)	(0.00779)	(0.0531)		
Med. conditions, children	−0.607	0.205	0.576	0.0321	−0.114		
	(0.414)	(0.151)	(0.272)	(0.0165)	(0.0774)		
	Part-time						
	(U, U)	(U, M)	(M, M)	(N, M)	(N, N)	(S, M)	(S, S)
Age	0.679	0.0353	−0.267	0.0101	0.0192	0.0640	0.188
	(0.0152)	(0.0397)	(0.109)	(0.00801)	(0.0170)	(0.0350)	(0.0790)
Black	−0.485	0.120	0.0287	0.109	−0.0155	0.761	−0.0162
	(0.317)	(0.456)	(0.0134)	(0.0936)	(0.762)	(0.403)	(0.735)
Hispanic	0.648	0.0236	0.0220	−0.166	−0.0138	0.0426	−0.0376
	(0.713)	(0.0114)	(0.0195)	(0.129)	(0.739)	(0.434)	(0.0164)
Children under 4	0.0769	0.0670	−0.229	0.0520	0.117	0.244	0.949
	(0.150)	(0.264)	(0.854)	(0.0502)	(0.199)	(0.172)	(0.755)
Med. conditions, mother	−0.263	−0.643	0.0122	−0.0146	−0.0222	−0.108	−0.302
	(0.152)	(0.335)	(0.474)	(0.0218)	(0.0525)	(0.0777)	(0.182)
Age of youngest child	0.116	−0.0921	−0.225	−0.0207	0.0586	−0.0711	0.301
	(0.0716)	(0.0523)	(0.0899)	(0.00938)	(0.0328)	(0.0357)	(0.120)
Med. conditions, children	−0.479	0.182	0.433	0.0379	−0.0915	0.127	−0.256
	(0.310)	(0.122)	(0.174)	(0.0180)	(0.0561)	(0.0651)	(0.152)
	Full-time						
	(U, U)	(U, M)	(M, M)	(N, M)	(N, N)	(S, M)	(S, S)
Age	−0.382	0.0213	−0.406	0.0119	0.0182	0.133	0.410
	(0.0268)	(0.0567)	(0.156)	(0.0143)	(0.0282)	(0.0572)	(0.144)
Black	−0.918	0.0618	0.0328	0.187	−0.0305	0.0183	−0.0532
	(0.548)	(0.712)	(0.0163)	(0.187)	(0.0151)	(0.0116)	(0.0161)
Hispanic	0.838	0.0298	0.0125	−0.142	−0.0283	−0.463	−0.121
	(0.926)	(0.0136)	(0.0232)	(0.318)	(0.0153)	(0.0136)	(0.0383)
Children under 4	−0.461	−0.0102	−0.0279	−0.214	−0.502	−0.740	−0.0251
	(0.345)	(0.618)	(0.0160)	(0.0908)	(0.374)	(0.327)	(0.0136)
Med. conditions, mother	−0.421	−0.899	0.0184	−0.116	0.0167	−0.179	−0.502
	(0.233)	(0.405)	(0.682)	(0.0381)	(0.0901)	(0.135)	(0.356)
Age of youngest child	0.179	−0.185	−0.378	−0.0541	0.0845	−0.236	0.668
	(0.104)	(0.0839)	(0.153)	(0.0205)	(0.0492)	(0.122)	(0.205)
Med. conditions, children	−0.825	0.336	0.672	0.0924	−0.150	0.394	−0.565
	(0.496)	(0.184)	(0.273)	(0.0343)	(0.0897)	(0.188)	(0.317)

Notes: Average marginal effects (in percent) of discrete changes in the observable characteristics, holding other variables constant at their actual values. U = uninsured, M = Medicaid, N = non-group health insurance, S = ESHI. The first entry refers to mother's health insurance status and the second to children's coverage. Block-bootstrap (on the state level) standard errors in parentheses.

mean and variance-covariance coefficients of the preference parameter distribution, i.e. the vectors δ^L etc. and the variance-covariance matrix corresponding to the preference shocks ξ_i^U (see Section 5.2.5 in the paper). The estimates show that women with young children value leisure more highly. Moreover, mother's and children's medical conditions increase the marginal utility of Medicaid and private health insurance coverage significantly as expected. Conditional on medical conditions, Medicaid yields a higher marginal utility than private health insurance. This finding implies that Medicaid stigma is not the reason for low take-up of Medicaid for the average eligible household.

Since the coefficients in Table 7 cannot be easily interpreted, I also report average marginal effects of the individual characteristics on the probability of choosing each of the four employment alternatives in Table 8.[6] Focussing on the larger effects, I find that more medical conditions of both mothers and children lead to a higher likelihood of choosing alternatives with Medicaid or private health insurance coverage. Moreover, single mothers with minority status are unlikely to hold full-time jobs with ESHI for both themselves and their children. Overall, these marginal effects reveal a substantial amount of heterogeneity. Modeling labor supply and health insurance choice as a function of observed and unobserved characteristics is hence necessary in order to obtain subgroup-specific estimates for the effects of health care reform on these choices.

C Government Program Policies and Data Sources

C.1 Medicaid

I show and describe the Medicaid eligibility rules for parents and children in the text (see equations (3) and (4)). The Medicaid eligibility thresholds for parents and children in different age groups, M_{it}^P and $M_{it}^{K,a}$, differ by state, year, and family size and completely describe the eligibility for this program.[7]

C.2 TANF

TANF rules are set by states and—with some simplifications—can be of either of two types:

$$TANF_{stf} = \max\left\{RP_{st}\left[BENSTD_{stf} - (E - DISREG_{st})\right], 0\right\}$$

[6] I obtain the average marginal effects by first calculating the marginal effect as the difference in predicted probabilities of choosing each employment alternative. Since the individual characteristics are discrete variables, I calculate differences in predicted probabilities based on a discrete change in the independent variables instead of approximating an infinitesimal change. Then I average these marginal effects over all individuals, time periods, and simulation draws.

[7] Sources for Medicaid thresholds: Sarah Hamersma kindly shared thresholds for parental Medicaid with me (see also Hamersma and Kim, 2009); for children's Medicaid: Kaiser Commission on Medicaid and the Uninsured, "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP," various years (available at http://www.kff.org/medicaid/index.cfm).

or

$$TANF_{stf} = \min\left\{\max\left\{RP_{st}\left[BENSTD_{stf} - (E - DISREG_{st})\right], 0\right\}, MAXBEN_{stf}\right\},$$

in state s, year t, and family size f, where RP_{st} is the ratable percentage (which can be above or below one), $BENSTD_{stf}$ is the benefit standard, E are monthly earnings, $DISREG_{st}$ is an earnings disregard, which can be expressed either as a dollar amount or a percentage, and $MAXBEN_{stf}$ is the maximum benefit. $BENSTD_{stf}$ and $MAXBEN_{stf}$ vary by family size. These rules are somewhat simplified, but capture the calculation of welfare benefits in most states accurately.[8]

In addition, there are requirements that families have to meet in order to be eligible for TANF. Most states have gross and net income or earnings tests, for example. In many cases, these tests coincide with the benefit calculation, i.e., families are eligible if $TANF_{stf} > 0$. Moreover, some states also impose asset tests. Since the MEPS data do not contain information on respondents' assets, I do not incorporate asset tests when imputing welfare benefits.

C.3 Food Stamps

Eligibility is determined by gross and net income tests. To be eligible, gross monthly income (GMI) has to be below 1.3 times the FPL, where GMI is defined as most cash income including TANF benefits and excludes non-cash and in-kind income. I assume that households have no unearned income so that GMI equals monthly family earnings plus TANF benefits. In addition, net monthly income (NMI) has to be below the FPL. NMI equals GMI minus the standard deduction (between $134 and $191 according to family size), 20 percent of earnings, the dependent care deduction ($200 for under two year olds, $175 for over two year olds), the medical deduction (maximum $35), a child support payment deduction (assumed to be zero), and an excess shelter deduction (maximum from $247 in 1996 to $431 in 2008). To simplify the calculation, I assume that all children are over two years old and set the medical and excess shelter deductions equal to their maximum amounts. Benefits are calculated as maximum benefit, which varies by family size, minus 0.3 times NMI. The food stamp program is a federal program so that benefits do not vary across states, but only over time.[9]

C.4 Earned Income Tax Credit (EITC)

The following parameters vary by number of children: credit rate (r_c^n), minimum income for maximum credit (Y_{min}^n), maximum credit (C_{max}^n), phaseout rate (r_p^n), beginning income for phaseout

[8]Source for TANF parameters: Urban Institute Welfare Rules Database (http://anfdata.urban.org/wrd/wrdwelcome.cfm).

[9]Source for food stamp parameters: United States Department of Agriculture: Characteristics of Food Stamp Households, Fiscal Years 1996 to 2007, Characteristics of Supplemental Nutrition Assistance Program Households, Fiscal Year 2008 to 2010. Available from http://www.fns.usda.gov/. Federal poverty line data available from http://aspe.hhs.gov/poverty/figures-fed-reg.shtml.

(Y^n_{beg}), and ending income for phaseout (Y^n_{end}), where $n = 0, 1, 2$ is the number of children (0, 1, and 2 or more).[10] The monthly tax credit given monthly earnings E is defined as

$$EITC = \frac{1}{12}\left[r^n_c 12E\mathbf{1}\left\{0 < 12E \le Y^n_{min}\right\} + C^n_{max}\mathbf{1}\left\{Y^n_{min} < 12E \le Y^n_{beg}\right\} \right.$$
$$\left. + \left[C^n_{max} - r^n_p\left(12E - Y^n_{beg}\right)\right]\mathbf{1}\left\{Y^n_{beg} < 12E \le Y^n_{end}\right\}\right].$$

Hence, a family is not eligible to receive the EITC if annual earnings are zero or exceed Y_{end}

C.5 Federal Income and Payroll Taxes

Annual taxable income is defined as

$$TI = 12E - ded_s - fs \times exem,$$

where E is monthly earnings, ded_s is the standard deduction, which varies by filing status, fs is family size, and $exem$ is the personal exemption. Possible filing status are single, married filing jointly, and head of household. MEPS data contain a variable that indicates a single mother's filing status. (She might file as married filing jointly if she is not yet divorced, for example.) Monthly tax payments are defined as

$$FIT = \frac{1}{12}\sum_{i=1}^{I}\tau_i \max\left\{\min\left\{TI - F^s_{i-1}, F^s_i - F^s_{i-1}\right\}, 0\right\},$$

where $I = 5$ (until 2001) or $I = 6$ (2002 and later) is the number of income brackets, τ_i is the tax rate in bracket i, F^s_i is the end point of bracket i, $F^s_0 = 0$, and $F^s_I = \infty$. The bracket end points but not the tax rates depend on filing status.[11]

The payroll tax between 1996 and 2008 was 7.65 percent (6.2 percent employee contribution to the Old-Age, Survivors, and Disability program and 1.45 percent for Medicare).[12]

C.6 Other Data Sources

Besides the policy variables described in this appendix I also use some other state-level variables. Fractions of firms offering ESHI, average ESHI premiums, and fractions of the premium paid by employers and employees, respectively, come from the Insurance Component (IC) of the MEPS. Summary statistics of the MEPS IC data at the state and year level are publicly available.[13] I obtain

[10]Source for EITC variables: Tax Policy Center Historical EITC Parameters (http://www.taxpolicycenter.org/taxfacts/Content/PDF/historical_eitc_parameters.pdf).

[11]Source for federal income tax variables: Tax Policy Center Individual Income Tax Parameters (Including Brackets), 1945-2011 (http://www.taxpolicycenter.org/taxfacts/Content/PDF/individual_rates.pdf).

[12]Source: Tax Policy Center Historical Social Security Tax Rates (http://www.taxpolicycenter.org/taxfacts/ Content/PDF/ssrate_historical.pdf)

[13]Source: Agency for Healthcare Research and Quality, Center for Financing, Access and Cost Trends. 1996 to 2006, 2008 Medical Expenditure Panel Survey-Insurance Component (http://www.meps.ahrq.

state unemployment rates and the consumer price index from the Bureau of Labor Statistics.[14] Finally, state minimum wages come from the Department of Labor.[15]

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[14]Sources: Bureau of Labor Statistics: Local Area Unemployment Statistics (http://www.bls.gov/lau/) and Consumer Price Index (ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt).

[15]Source: United States Department of Labor: Changes in Basic Minimum Wages in Non-Farm Employment Under State Law: Selected Years 1968 to 2008 (http://www.dol.gov/whd/state/stateMinWageHis.htm).